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An Optimal Lubrication Oil Replacement Method Based on Selected Oil Field Data

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ABSTRACT The regular replacement of lubricating oil plays a key role in improving machine reliability and reducing unexpected failures of an oil lubricated system. This paper proposes a condition-based maintenance problem with selected oil field data to determine the optimal time of the lubricating oil replacement. The selected oil field data contain health information about the lubricating oil, so the degradation state of the oil can be predicted and the future health condition can be evaluated. The proposed lubricating oil replacement problem is modeled with the evaluated oil health condition in a Markov decision process framework and then, a method for constructing a health index for the lubricating oil is proposed based on information theory to fuse the multiple oil field data and build a degradation progression prediction model. Finally, the proposed method for condition-based lubricating oil replacement is illustrated in a practical case study. The possible applications of an optimal policy for lubricating oil replacement are much wider. For instance, the method can be used as an input to optimize an operational plan and further reduce the maintenance costs.

INDEX TERMS Lubricating oil, replacement, material wear and system degradation, system degradation model, health index, prognostics, oil field data.

I. INTRODUCTION

Lubricating oil is used to reduce wear in friction couplings, improve machine reliability and reduce the economic costs associated with possible future unplanned maintenance. Therefore, an oil lubrication system should be monitored regularly, and the oil should be replaced in time to extend the period over which the machine operates in a healthy state [1]. Recently, condition monitoring (CM) of lubricating oil has become an important research field and has played a vital role in industry, see, e.g., [2]–[9] and the references therein. Oil field information has been utilized to estimate the health condition of the lubricating oil, but to our knowledge, an optimal oil replacement policy that use such oil field information to prevent unexpected failures has not been developed in the literature. The paper aims to address an optimal replacement problem for oil lubrication systems with selected oil field data to determine the optimal lubricating oil replacement time.

As a machine operates, wear debris spalling from each wear component is uniformly mixed in lubricating oil, and the level of wear debris is one of the most common types of degradation features that can be used to estimate the severity of the underlying oil degradation [5], [6]. The concentration of wear debris has been observed from spectral oil analysis during the inspection epoch [10]. Moreover, metal wear debris accumulates in the lubricating oil, and the concentration increases, which leads to lubricating oil degradation [7], [8]. Using wear debris, many researchers have presented indicators that can characterize the severity of the underlying degradation process, where the lubricating oil considered to have failed when these spectral oil data cross a predetermined threshold [11], [12]. With the degradation state assessed, timely lubricating oil replacement will essentially avoid severe operation conditions and enable a predictive maintenance strategy, which can lead to fewer unexpected failures [13].

Although spectral oil data have been used in practice for many years to evaluate lubricating oil degradation and predict its residual life (RL), see, e.g., [5], [9] and the reference therein, little work has been done using spectral oil data to build a degradation model for the purpose of modeling the oil replacement problem. In the prognostics and health management (PHM) area, degradation modeling and RL prediction were applied to lubricating oil contaminated with debris by

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applying a stochastic model using a Wiener process (WP) [8], [9] and, extracting a composite health index (HI) based on multiple selected spectral oil data [10], [14]. A comprehensive review of the application of different approaches in oil-based PHM can be found in [15] and the references therein. To our knowledge, no oil replacement decision models have been developed in the literature that can be utilized for the determination of the optimal oil replacement time.

In this paper, we present a condition-based maintenance (CBM) problem to determine the optimal lubricating oil replacement time by proposing a new HI-based degradation modeling framework using selected spectral oil data. In the proposed framework, a WP-based degradation process is established to model the constructed HI of the lubricating oil. The HI is constructed using a weighted average of selection of degradation data with allocation steps for the weight coefficients that ensure the accuracy of the degradation state evaluation and reduce the difficulties of the parameter estimation. This is of practical significance for the evaluation of the degradation state of lubricating oil and determining the optimal oil replacement time and, thus, is one contribution of this paper. Based on the evaluated oil health condition, the lubricating oil replacement problem is then modeled in a Markov decision process (MDP) framework and a control limit of the replacement threshold can be determined, which is another contribution of this paper. To illustrate the proposed method in this paper, a case study is provided for oil lubrication systems in power shift steering transmission (PSST) systems.

The framework of the optimal lubricating oil replacement methodology is shown in Figure 1. The rest of this paper is organized as follows. Section II describes the motivation of the lubricating oil replacement problem. In section III, a method for constructing the HI for lubricating oil is developed and the oil degradation modeling framework is presented based on the constructed HI. Section IV provides an illustrative case study for several PSST systems. In section V, the conclusions of this work and some future research is provided.

II. MOTIVATION OF THE LUBRICATING OIL REPLACEMENT PROBLEM

A description of the lubricating oil replacement problem consider in this paper is first provided in this section. This paper considers an oil lubrication system that is monitored using regular oil spectral analysis. Lubricating oil deteriorates over time in severe and various working conditions and the associated degradation process $\{L(t), t \geq 0\}$ is periodically analyzed to evaluate the severity of the lubricating oil degradation. The degradation process $\{L(t), t \geq 0\}$ is assumed to have an increasing but not necessarily monotonic trend. The lubricating oil is regarded as having reached a failure state if the degradation process reaches a failure threshold ξ' that is usually predetermined by practitioners. Once the failure is revealed, the oil lubrication system is considered to be operating in an abnormal working state and cannot

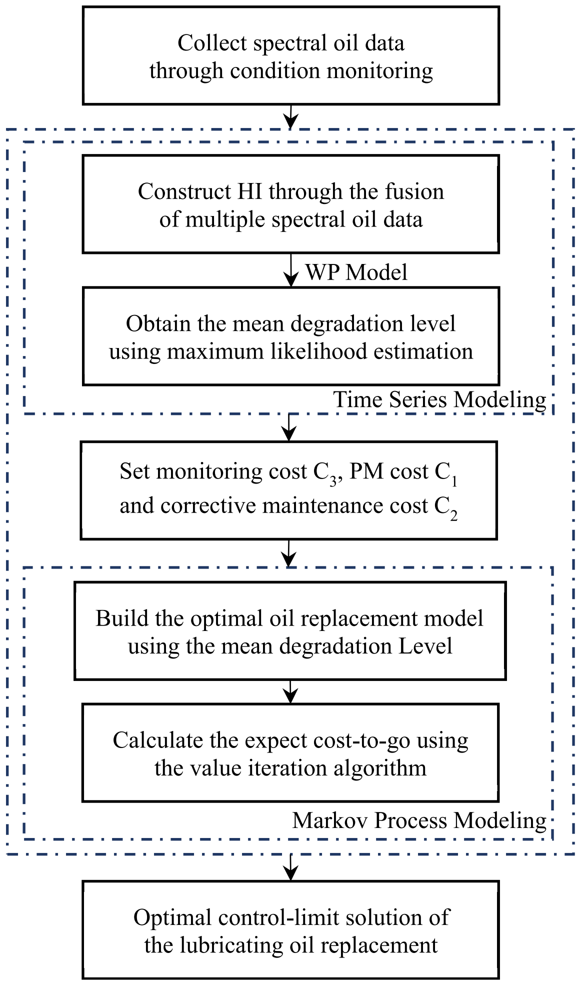

FIGURE 1. **HI-based degradation modeling framework for oil replacement.**

function as required. The failure of the lubricating oil is not self-evident and can only be detected by oil analysis. For each oil sampling, if the degradation process reaches the predetermined threshold ξ', corrective maintenance is performed immediately. Alternatively, the maintenance decision must be made based on the current degradation level to determine whether to preventively replace the lubricating oil or let it operate until the next oil sampling. It is assumed that all lubricating oil replacement actions are perform immediately and that preventive replacement and corrective replacement are perfect, which can restore the oil lubrication system to an undegraded state. Considering that the oil sampling interval is fixed in practical applications, the oil sampling interval will not be optimized [16]. Thus, the aim of this research is to find the optimal policy for lubricating oil replacement to minimize the total operating cost of the monitored oil lubrication system.

Based on the mentioned description of the lubricating oil replacement problem, when the machine is operating, the associated spectral oil data are utilized to measure the lubricating oil degradation level $\{L(t), t \geq 0\}$ at time $t_k, k = 0, 1, \ldots$ in a near-real-time manner, with $t_k = k\Delta t$ and Δt

being the oil sampling epoch. Without loss of generality, each oil sampling and the corresponding oil analysis process has a cost of c_3. If the degradation level at each $t_k = k\Delta t$ does not reach the failure threshold ξ', the maintenance decision is twofold. One decision is to replace the lubricating oil, which is a preventive maintenance (PM) action on the oil lubrication system, with an immediate cost c_1, which will restore the lubricating oil to an undegraded state. The other decision is to do nothing until the next oil sampling time. If the oil lubrication system operates continuously, the risk of a machine failure in the next oil sampling epoch may occur where the degradation level is above the threshold, the system failure rate will increase sharply and the system will soon fail such that it no longer functions [5], [8]. The PSST system presented in this paper, which is a key component in military armored vehicles, has high reliability requirements because of the severe operation conditions and special applications. In this case, it is necessary to perform corrective maintenance, including a system-dismantling inspection, lubricating oil replacement and a possible component replacement, with a failure cost $c_2(c_2 > c_1)$, which makes the lubricating oil return to an undegraded state. Above all, the concerned lubricating oil replacement problem can be formulated in the MDP framework based on the above description.

The state space of the MDP is defined as $\mathrm{W} = (\mathrm{K}, \mathfrak{R})$, where $\mathrm{K} = \{0, 1, \ldots, \}$ denotes the oil sampling epoch set and $\mathfrak{R}$ is a set of real numbers. Let $L_k \in \mathfrak{R})$ be the stochastic spectral oil data of the oil lubrication system at t_k, where $t_k = k\Delta t$ and $k \in \mathrm{K}$. Furthermore, the realization of L_k is represented as l_k, which refers to the observed spectral oil data. To formulate the lubricating oil replacement problem, $0 < \lambda < 1$ is set as a discount factor and $V(k, l_k)$ is set as the total expected discounted cost function starting from the operation state $(k, l_k) \in \mathrm{W}$. Then, in the MDP framework, the optimality equations of the lubricating oil replacement problem are formulated for all states $(k, l_k) \in \mathrm{W}$ as

$$V(k, l_k) = \begin{cases} c_2 + V(0, l_0) & l_k > \xi' \\ min\{c_1 + V(0, l_0)\,, \\ \quad \lambda(c_3 + E[V(k+1, L)])\}\,, & l_k \leq \xi' \end{cases} \tag{1}$$

where l_0 is the initial inspection, L is a random degradation variable representing the stochastic spectral oil data at the next inspection time, i.e., $L = L_{k+1}$. $E[V(k+1, L)]$ is the expected cost-to-go, which is given as

$$\begin{aligned} E[V(k+1, L)] &= \int_{x\in\mathfrak{R}} (V(k+1, x)) f_L(x) d_x \\ &= \int_{x\in\mathfrak{R}} (V(k+1, x)) dF_L(x) \end{aligned} \tag{2}$$

where $f_L(x)$ is the probability density function (PDF) of L and $F_L(x)$ is the cumulative distribution function (CDF) of L.

The logic of equation (1) is given as follows: If the current degradation state l_k at the sampling time k crosses the threshold ξ', corrective maintenance will carry out with cost c_2 and the lubricating oil renews to the undegraded state; otherwise, if l_k is below the failure threshold, PM can either be performed or the machine can be allowed to operate until the next inspection time, depending on the associated minimal cost. In this case, if PM is performed, a cost c_1 is incurred to renew the lubricating oil. Otherwise, we have $E[V(k+1, L)]$ with an additional inspection cost of c_3. Then, a control limit of the threshold should be specified for maintenance.

Equation (1) can be numerically solved using a value iteration algorithm. From the description of equation (1), it is concluded that the optimal lubricating oil replacement policy is heavily dependent on the oil future degradation state L, which can be predicted by oil degradation modeling. Thus, in the following, a new degradation modeling framework is proposed based on multiple selected spectral oil data to predict L and formulate the PDF $f_L(x)$ and the CDF $F_L(x)$. The aim is to estimate the mean degradation level $E[\mathrm{V}(k+1, L)]$ of the lubricating oil and obtain the optimal oil replacement policy.

III. NEWLY DEVELOPED DEGRADATION MODELING FRAMEWORK

In recent years, stochastic processes have been used in practice to model the evolution of lubricating oil degradation and its relationship with oil spectral analysis [17], [18]. In this paper, the degradation process of the lubricating oil is represented as $\{L(t), t \geq 0\}$, where $L(t)$ denotes the degradation state of the lubricating oil at time t. This type of model has been widely used to model the degradation process of lubricating oil (see, e.g., [16]–[19]). However, for an oil lubrication system that is monitored using oil spectral analysis, the main limitation of these studies is that the developed models only consider single elements (e.g., Fe, Cu and Mo, [19]) in the wear debris concentration data in spectral oil analysis. In reality, various types of wear debris produced from different friction couplings are uniformly mixed in the lubricating oil. In this sense, single-element concentration data alone are insufficient for representing the lubricating oil degradation process, causing inaccuracy in the degradation modeling and prognostics [20], [21]. Therefore, a composite HI must be constructed to characterize the degradation of the lubricating oil through a fusion of multiple CM data, which can be used for degradation modeling and RL prediction.

A. HI CONSTRUCTION METHODOLOGY

With the newly developed optimal lubricating oil replacement framework, we present a method to constructed the HI to better characterize the degree of the degradation of the lubricating oil through a fusion of multiple spectral oil data. Compared to relying solely on spectral oil data, this HI construction method can lead to a reasonable degradation model and an accurate RL prediction. The HI is constructed using a weighted average function with a selection of spectral oil data with allocation steps for the weight parameters, represented as

$$d_j = \boldsymbol{X_{i,j}\omega'} \tag{3}$$

where $\boldsymbol{X_{i,j}}$ represents the vector for the selected spectral oil data i in the sampling epoch j, $\boldsymbol{\omega} \in R^{N\times 1}$ is a vector of the weight parameters used to measure the relative importance of each selected spectral oil datum and N is the number of selected spectral oil data; $\boldsymbol{\omega}'\boldsymbol{M}'\mathbf{1} = \mathbf{1}$, where $\boldsymbol{M} \in R^{N\times N}$ is a diagonal matrix representing the degradation trend of the lubricating oil, and the diagonal element is 1 when the corresponding selected spectral oil data are increasing as the system operates and vice versa.

Remark 1: It is observed from equation (3) that the HI is a weighted average of all selected spectral oil data using the vector $\boldsymbol{\omega}$ to measure the relative contribution rate of each spectral oil datum to the lubricating oil degradation. The assumption of linearity is not suitable for all cases, and nonlinear functions may have to be used in other cases.

With the above construction, degradation data should be selected as the input to construct a composite HI. To do this, a degradation data selection method is developed based on source entropy. It is assumed that the spectral oil datum of the ith element at t_j inspection time is denoted as $y_{i,j}$, which represents the measurement of the target degradation data $x_{i,j}$ with noise. All of the spectral oil data from CM are represented by $\boldsymbol{Y_{i,j}} = \{y_{i,j}|i = 1, 2, \ldots, N; j = 1, 2, \ldots, M\}$. Then, the target degradation dataset $\boldsymbol{X_i}$ can be characterized by the probability distribution $p_i(\boldsymbol{X_i})$ estimated from the spectral oil dataset $\boldsymbol{Y_i}$. Then, the information volume of the spectral oil dataset is measured using the Shannon entropy, represented as

$$H = -\sum\nolimits_{i=1}^{N} p_i(x)\log p_i(x) \tag{4}$$

where $p_i(x)$ is the probability of the ith condition and N is the number of conditions of the process $\boldsymbol{X_i}$.

Remark 2: It is noted that 15 types of main element concentrations are obtained from oil spectral analysis, and different element concentrations have different physical meanings [19], [22]. In engineering, degradation data series that contain more information during system operation are of interest. Based on this criterion, the source entropy, which can describe the information volume in each set of a data series, is used to select the appropriate degradation data [23], [24]. The objective is to quantitatively select degradation data that contain more health information.

Based on the selected degradation data, the relative importance of different spectral oil data from various sources should then be measured. To do this, a weight allocation method is developed based on permutation entropy. In information theory, the data series X_i has $M!$ possible permutation order types. Then, the relative frequency of each possible permutation type π is represented as

$$p\,(\pi) = \frac{\#\{t|0 \le j \le M-n, \left(x_{j+1}, \ldots, x_{j+n}\right) \, has\ type\ \pi\}}{M-n+1} \tag{5}$$

where n is the number of possible order types. When the order is $n \geq 2$, the permutation entropy is represented as

$$H\,(n) = -\sum p(\pi)logp(\pi) \tag{6}$$

Among these permutation entropies, the permutation entropy 2! is widely used in engineering for its useful mathematical properties and clear concept, represented as

$$H\,(2) = -plogp - (1-p)log(1-p) \tag{7}$$

where p is the monotonic probability of order $n = 2$. If p represents a probability with increasing trend, then $1 - p$ represents a probability with a decreasing trend. Thus, the increasing or decreasing trend of the degradation data is measured using the 2! permutation entropy [10], [25].

Remark 3: In engineering, different metal wear debris have different weights contributing to the lubricating oil degradation. In the area of PHM, degradation signals that have a clear increasing or decreasing trend are strongly related to the system degradation and fault occurrence, while others may not be so strongly related. Based on this criterion, the permutation entropy, which can measure the degree of the monotonic in each set of data series [10], [22], is used to allocate the weights in the HI construction. The objective is to determine the weight parameter of each set of degradation data by measuring the relative scale of the permutation entropy from the selected spectral oil data.

It can be clearly concluded from equation (7) that $0 \leq H\,(2) \leq 1$, where the lower bound is obtained for an increasing or decreasing degradation data series. Specifically, the smaller permutation entropy $H\,(2)$ of the selected spectral oil data has a better monotonic characteristic. In addition, there may be more contributions to lubricating oil degradation [21], [26]. Therefore, the weight of each selected degradation datum in the framework of the HI construction is defined based on the proportion of the permutation entropy, represented as

$$w_i = \frac{1 - H_i}{N - \sum_{i=1}^{N} H_i} \tag{8}$$

Remark 4: The weight of each selected degradation datum is determined according to the degradation trend represented by the permutation entropy. The basic starting point for the HI construction is that if a degradation datum exhibits a larger degradation trend, this degradation datum contributes more to the system degradation. That is, a smaller permutation entropy means a greater weight

Figure 2 shows a flow chart of the HI construction methodology, which includes spectral oil data selection, weight parameter allocation and degradation data fusion steps. Using the method, a degradation model of the lubricating oil can be established and the condition of the oil can be evaluated based on the constructed HI from multiple spectral oil data.

B. WP-BASED DEGRADATION MODEL

In engineering, the WP-based model is extensively applied in modeling degradation processes due to its clear concept,

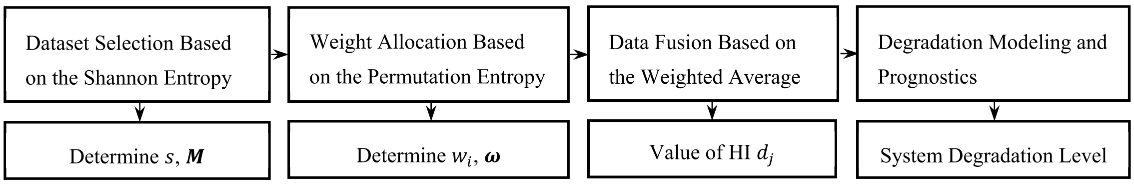

FIGURE 2. Flowchart of the HI construction methodology.

in which the associated drift coefficient is to model the degradation rate of the system [27]. Therefore, this paper considers a WP to represent the degradation model of the lubricating oil $\{L(t), t \geq 0\}$, represented as

$$L(t) = L(0) + \theta t + \sigma B(t) \tag{9}$$

where $L(0)$ is the initial degradation state, θ represents the unknown drift coefficient that characterizes the degradation rate of the lubricating oil, $B(t)$ is a standard Brownian movement (BM), $\sigma B(t) \sim N(0, \sigma^2 t)$, and σ represents the diffusion coefficient. This BM part is used to denote the dynamics of the lubricating oil degradation process.

The basic mechanism behind the degradation process $\{L(t), t \geq 0\}$ is that the degradation of the lubricating oil can increase or decrease gradually with the operation of the oil lubrication system. The degradation increments within a small-time interval, behaving similarly to a random walk of small particles in air or a fluid. Therefore, utilizing a WP-based degradation model means that the system degradation process is nonmonotonic, in accordance with the characteristics of the variation of the wear debris concentration in lubricating oil. In addition, the WP-based degradation model implies that the degradation path is linear in time, i.e., $EL(t) = L(0) + \theta t$. Therefore, the drift coefficient θ is closely related to the degradation progression. For nonlinear cases, a logarithm transformation or time-scale transformation can be used to transform the nonlinear processes to linear processes, and then, the linear WP in equation (9) is used.

We know from equation (9) that the mean degradation level is governed by θ, while the diffusion parameter σ partially represents the uncertainty in the degradation process. Thus, σ is assumed be determined by the degradation histories and is not updated once it is estimated, and θ is updated using the constructed HI up to the current time. Admittedly, σ can be updated in theory, but this is not the focus of this research.

With the above description, the parameter θ in the degradation model can be estimated and updated using the constructed HI up to the current time. The constructed HIs $l_0, l_1, \ldots, l_k$ up to the sampling epoch k have been obtained using the method in the last section (denoted by $l_{0:k} = \{l_0, l_1, \ldots, l_k\}$, e.g., with the constructed HI l_k for L_k and $l_k > l_0$. Based on the obtained HI $l_{0:k}$ up to the sampling epoch k, the maximum likelihood estimation (MLE) $\hat{\theta}'_{\mathrm{ML}}(k, l_k)$ of θ at each sampling epoch k can be obtained, represented as

$$\hat{\theta}'_{\mathrm{ML}}(k, l_k) = \frac{l_k - l_0}{k\Delta t} \tag{10}$$

which is also unbiased. See article [28] for more details on the estimation steps of the MLE method.

Based on the constructed HI $l_{0:k}$ up to the sampling epoch k conditional on the MLE estimator $\theta = \hat{\theta}'_{\mathrm{ML}}(k, l_k)$, the estimated conditional distribution of the degradation level L at the next inspection time is normally distributed with the PDF $f_{L|l_{0:k},\theta = \hat{\theta}'_{\mathrm{ML}}(k, l_k)}(X)$ and the CDF $F_{L|l_{0:k},\theta = \hat{\theta}'_{\mathrm{ML}}(k, l_k)}(X)$ as

$$\begin{aligned} f_{L|l_{0:k},\theta = \hat{\theta}'_{\mathrm{ML}}(k, l_k)}(X) &= \frac{1}{\tilde{\sigma}\sqrt{2\pi}}\exp\left(-\frac{(x - \tilde{u}(k, l_k))^2}{2\tilde{\sigma}^2}\right), \quad x \in \Re \end{aligned} \tag{11}$$

$$F_{L|l_{0:k},\theta = \hat{\theta}'_{\mathrm{ML}}(k, l_k)}(X) = \Phi\left(\frac{x - \tilde{u}(k, l_k)}{\tilde{\sigma}}\right) \tag{12}$$

where the mean and the variance are given as follows, respectively:

$$\tilde{u}(k, l_k) = l_k + \hat{\theta}'_{ML}(k, l_k)\Delta t = l_k + \frac{l_k - l_0}{k} \tag{13}$$

$$\tilde{\sigma}^2 = \sigma^2 \Delta t \tag{14}$$

It is observed from equations (10-14) that the predicted distribution of the degradation level L in the next sampling epoch is updated at each time when new spectral oil data are obtained. When the drift coefficient θ is estimated, the associated HI L at the next inspection time can be derived according to the properties of the WP, and is given by

$$L = l_k + \hat{\theta}'_{\mathrm{ML}}(k, l_k)(t_{k+1} - t_k) + \hat{\sigma}B(t_{k+1}) - \hat{\sigma}B(t_k) \tag{15}$$

Based on the formulation of L in equation (15), the optimal replacement policy of the oil lubrication system can be established.

IV. A CASE STUDY

A practical case study for an oil lubrication system of a PSST system is provided in this section to illustrate the entire procedure of the proposed optimal lubricating oil replacement method and to investigate the results and application of the proposed method. The power transmission system is a key device in tracked armored vehicles and large engineering machinery, and PSST plays a crucial role in the system [9], [10]. PSST operates under cyclic multigear, load-varying and multispeed conditions, and contamination in the lubricating oil causes approximately 70% of operation faults,

TABLE 1. Data of the oil spectral analysis for one PSST test (unit: ppm).

Sample	Time/Mh	Zn	Ca	Cr	Ni	Sn	Na	Cu	Al	Mn	Pb	Mg	Fe	P	Mo	Si
1	5	1030	2357	0.5	0.2	0	15.7	10.2	3.1	0.2	6.2	19.2	10.8	1033	0.1	3.8
2	10	1019	2545	0.6	0.4	0	16.2	10.4	3.1	0.6	6.3	18.5	17.1	1027	0.1	5.1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
36	180	1034	2412	5.4	9.9	0	15.6	17.8	3.4	4.4	7.0	18.2	636	1022	0.9	4.9

TABLE 2. Source entropies of the element concentration data (unit: bits).

Element	Zn	Ca	Cr	Ni	Sn	Na	Cu	Al	Mn	Pb	Mg	Fe	P	Mo	Si
Value	0.472	0.637	6.37	6.52	0	0.276	5.42	0.0846	2.35	0.213	0.157	7.262	0.354	4.83	0.186

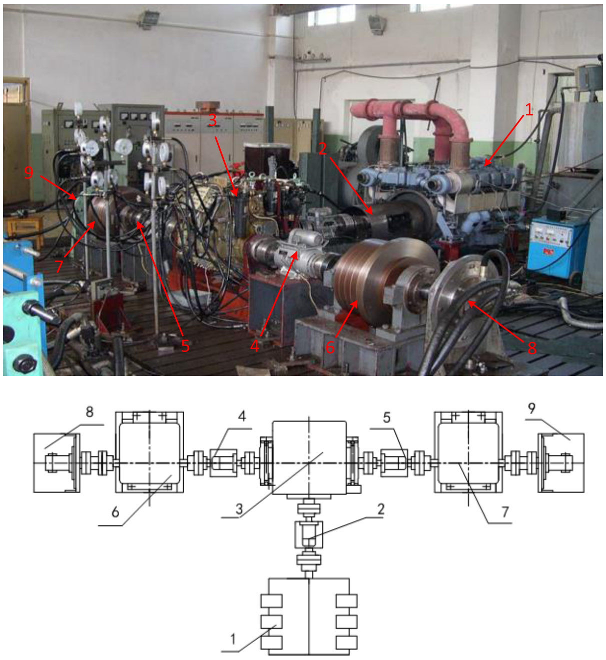

FIGURE 3. Life-cycle test bed of the PSST 1: Diesel engine. 2, 4, 5: Torque and speed sensors.3: PSST. 6, 7: Inertia discs. 8, 9: Loading piston pump.

of which more than 50% are related to metal wear debris [8]. Hence, routine CM enabling PSST operate must be carried out to monitor the system health. As such, it is concluded that wear debris in lubricating oil is difficult to directly observe and can be indirectly assessed via lubricant condition monitoring (LCM). During the operation of PSST, metal wear debris accumulates in the lubricating oil, which accelerates the wear of the friction couplings and leads to degradation of the lubricating oil. Therefore, the element concentration data from LCM is often used as an indicator to evaluate the health status of the lubricating oil and make a replacement decision based on the current health state.

A. ORIGIN OF THE DATA

In this case, the element concentration data in [20] is used for an illustration. The associated oil field data were obtained for the reliability analysis from a test of the PSST system (Figure 3 and Figure 4). All of the tested PSST units were tested under cyclic multigear, load-varying and multispeed conditions that were prescribed by the manufacturer and

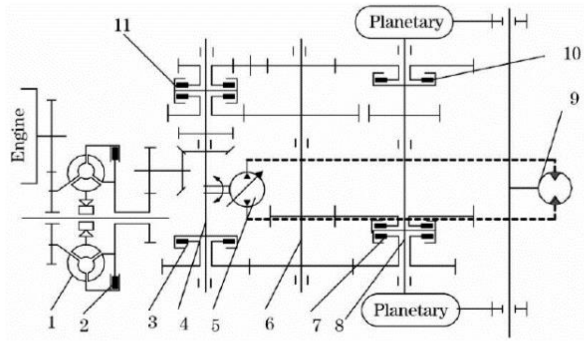

FIGURE 4. Sketch of the PSST 1: Hydraulic torque convertor. 2: CV clutch.3: CH clutch. 4: First shaft. 5: Steering pump. 6: Second shaft. 7: C1C2 clutch. 8: Third shaft. 9: Steering motor. 10: C3 clutch. 11: CLCR clutch.

defined by the owner. A detailed description of the procedure for the sampling and analysis processes can be found in [9].

We possess oil field data consisting of more than one thousand samples collected over a period of more than 10 years. The associated dataset used in this paper consists of 2 training units and 1 testing unit. Due to space restrictions, the spectral oil data of one PSST system are shown in Table 1.

Using these element concentration data, the degradation model can be established and then the degradation level of the lubricating oil can be determined. However, not all the elements can have the same contribution to oil degradation. Thus, in the next section, the element concentration data will be fused to construct a composite HI that can be used to characterize the degradation level of the lubricating oil.

B. HI CONSTRUCTION

Using the abovementioned element concentration data, the degradation data are selected based on the fact that the element concentration contains more health information. The source entropies of the measured element concentration data sets are shown in Table 2.

The greater source entropy values of the time series data contain more information, as illustrated in Remark 2. Based on this criterion, 6 (i.e., $N = 6$) spectral oil data samples are selected, namely, Fe, Cr, Ni, Cu, Mn and Mo. Correspondingly, the diagonal elements of $\boldsymbol{M}$ are set as $[1, 1, 1, 1, 1, 1]'$ based on the degradation trend. The selected 6 degradation data samples are shown in Figure 5.

The rationality of our selection can also be verified using a material analysis of the wear components (Table 3).

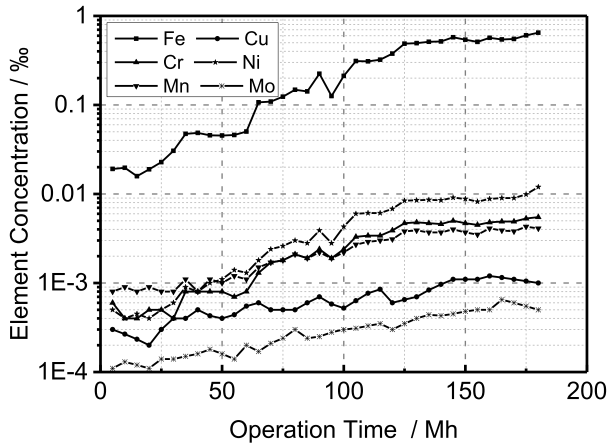

FIGURE 5. Curves for the degradation data.

TABLE 3. Metal element of the friction pair in PSST system.

Component	Friction Pair	Element
Wet clutch	Internal toothed friction plate	**Cu**, Pb
	External toothed steel disc	**Fe**, **Mn**
Transmission gear		**Fe**, **Cr**, **Ni**
Rotary sealing	Sealing ring	**Fe**, Si, **Mn**, **Mo**
Bearing	Distributing device	**Fe**, Si, **Cr**
	Rolling needle	**Fe**, **Cr**
	Caulking ring	**Cu**
Conflux planetary gear train	Planetary shaft	**Fe**, **Cr**, **Ni**
	Rolling needle	**Fe**, **Cr**
	Caulking ring	**Fe**, Pb
	Planetary wheel	**Fe**, **Cr**, **Ni**

TABLE 4. Permutation entropies (2!) of the selected degradation data (unit: bits).

Element	Cr	Ni	Cu	Mn	Fe	Mo
$H(2)$	0.7362	0.7869	0.9681	0.9975	0.5538	0.9826
w_i	0.2776	0.2186	0.0327	0.0026	0.4577	0.0178

Clearly, the 6 selected element concentration data samples contain the main material of the moving components of the PSST system considered in this paper. Thus, the degradation of the Lubrication oil is assumed to be governed by the oil spectral data, and this assumption is valid for every PSST system tested, as we (and other researchers) analyzed in [5], [7], [9]. Thus, the selected degradation will be used to build the degradation model of the oil lubrication system.

The degradation data with a clear increasing or decreasing trend are strongly related to the Lubrication oil degradation, as illustrated in Remark 3. Based on this criterion, the 2! permutation entropy values are calculated with equation (7), and the weight of each degradation dataset for data fusion is further calculated by equation (8), as shown in Table 4.

In the proposed HI construction method, the weight parameters of each degradation dataset report are measured based on the 2! permutation entropy, and at present, the selected multiple oil spectra can be fused with (equation 1) to construct a composite HI. The HIs at each sampling time point are shown in Table 5.

TABLE 5. HI of PSST.

t_j/Mh	x_j	t_j/Mh	x_j
5	0.092	160	0.728
10	0.229	165	0.732
15	0.221	170	0.748
20	0.226	175	0.762
…	…	180	0.786

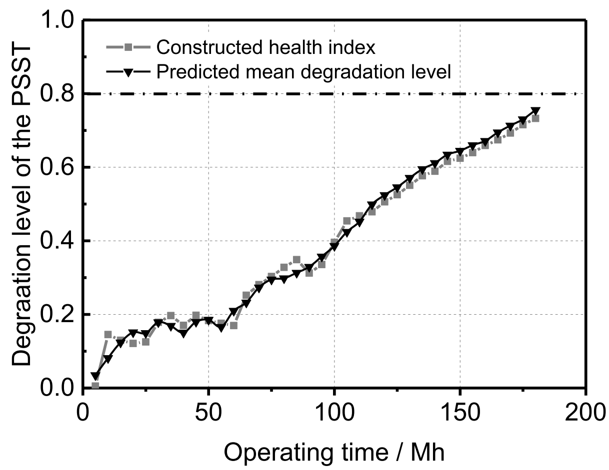

FIGURE 6. Constructed HI and the predicted degradation level.

The Lubrication oil is considered to have failed if the HI reaches a predetermined threshold ξ', which in this case is 0.8. This setting is predetermined by using statistical analysis of historical failure data [29], [30].

C. PREDICTION RESULTS

Based on the constructed HI of the Lubrication oil, the parameters in the model can be estimated based on the MLE method. To do so, we use the associated HI of PSST 1 and PSST 2 to initialize the degradation model, while the constructed HI of the PSST 3 is used for the validation of the established model. As such, the estimated parameters of the degradation model are $\theta_0 = 3.185 \times 10^{-3}$ and $\sigma^2 = 9.532 \times 10^{-4}$, which will be used as the initialization of the validation case. Conditional on the initialized model parameter, the estimated parameters $\hat{\theta}'_{ML}(k, l_k)$ at each sampling epoch $k(k > 0)$ and the predicted degradation level L at the next epoch is obtained. Figure 6 shows the predicted mean HI $\tilde{u}(k, l_k)$. The predicted mean degradation curve fits well to the actual constructed HI.

Using the predicted degradation level of the Lubrication oil, an optimal control limit of the Lubrication oil replacement policy can be calculated. Based on some real engineering considerations, we set $c_1 = 3000$RMB, $c_2 = 5000$RMB, $c_3 = 50$RMB, and the discount factor to be $\lambda = 0.99$. Then, by using a monotonic value iteration algorithm, the optimal control limit for a preventive Lubrication oil replacement decision is determined with the estimated model parameters and cost parameters. Figure 7 shows the optimal Lubrication

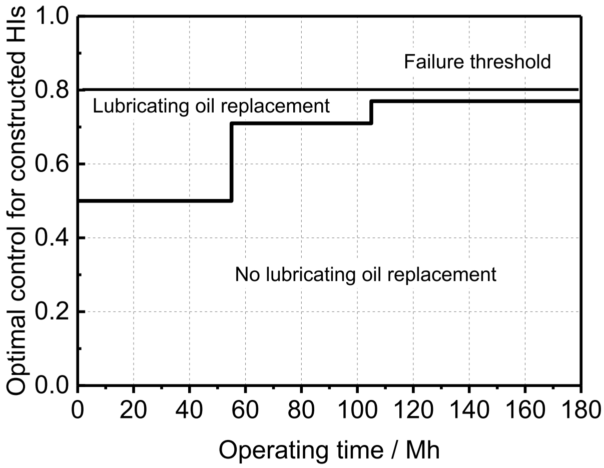

FIGURE 7. Control limit of the Lubrication oil replacement.

oil replacement policy with an optimal maintenance cost of $V^*(0, l_0) = 26338.67$RMB. Figure 7 shows that the optimal control limit monotonically increases with the PSST operation. In addition, the optimal control limits only change little at different operation time points. These characteristics make the preventive Lubrication oil replacement east to implement in practice and are consistent with typical solutions of the MDP.

In Figure 7, the step line is the optimal control limit of the predictive replacement for the HIs of the Lubrication oil for different ages of the PSST. If the constructed HI does not cross this control limit, the optimal maintenance decision is to continue the PSST operation and not replace the Lubrication oil; otherwise, the optimal maintenance decision is to preventively renew the Lubrication oil with a replacement.

In Figures 6 and 7, the estimation of the model parameters updates with the machine operation since the proposed methodology resolves at each sampling epoch and thus the Lubrication oil replacement policy with the newly constructed HI. It is noted that the stochastic model is only utilized to approximate the actual constructed HI and does not completely replicate the actual Lubrication oil degradation levels. As a result, the parameters of the established degradation model are updated dynamically with the machine operation and the corresponding Lubrication oil replacement policy will also be updated but will not converge for different oil sampling epochs, as shown in Figure 7. However, according to the theory of the MDP, if the constructed HIs can be modeled well by a WP and the model parameters change little, the replacement policy of the Lubrication oil converges to an optimal value [31]. This phenomenon is reflected by the parameter estimations and the prediction results, since Figure 6 shows the convergence of the degradation rate, while Figure 7 indicates the convergence of the optimal replacement of the Lubrication oil after 105 Mh. The logic in these findings is that the output rate and the filtration rate of the wear debris are balanced after 105 Mh and can be reproduced very well through the proposed WP model, as shown in Figure 6. Thus, the process of updating the parameters of the optimal oil replacement policy could be stopped when the model parameter estimation converges in the practical applications.

V. DISCUSSIONS AND CONCLUSION

The regular replacement of Lubrication oil plays a key role in improving machine reliability and reducing unexpected failures of an oil lubricated system. This paper studies a CBM problem with selected oil field information, namely, spectral oil data, for the determination of the optimal Lubrication oil replacement time. The selected spectral oil data contain health information about the Lubrication oil, so the condition of the oil can be estimated and the future degradation progression can be predicted. Using the observed spectral oil data, a new HI construction method for Lubrication oil based on information theory is proposed and then a Lubrication oil replacement problem is formulated in the MDP framework. To illustrate the proposed method in this paper, a case study is provided for oil lubrication systems in PSST systems.

The presented results are of practical significance to determining optimal Lubrication oil replacement decisions and thus, constitute one of the main contributions of this paper. The proposed HI-based degradation model ensures the accuracy of the degradation state evaluation and reduces the difficulties of the parameter estimation. which is another main contribution of this paper. In addition, the possible applications of the proposed optimal Lubrication oil replacement policy are much wider. For instance, the method can be used as an input in the optimization of a mission plan and further reduce the maintenance costs. The obtained outcomes also complement the approaches of CBM involving indirect CM of the technical condition of a system, for example in the works of Yan *et al.* [14], Zheng *et al.* [8], and Zhu *et al.* [4]. Following the conclusions presented in this paper, previous approaches might be improved when they are used for wear fault detection, inspection interval optimization, and other applications in the area of PHM.

The main contribution of this paper not only establishes a new direction in the CM and predictive maintenance of oil lubricated systems by using selected oil field data but also opens up possibilities for the analysis of other important diagnostic information. There are several important directions deserving future research. First, other constraints such as the system reliability may have to be considered in optimal replacement policies. Second, a nonlinear degradation model may have to be used when addressing other cases. Third, the measurement errors of the oil analysis process should be introduced in future research.

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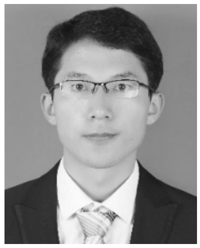

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